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Author(s): Jenkins, Cody David

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Bearing Fault Detection and Wear Estimation Using Machine Learning

Cody Jenkins

[1]Start Up and Commissioning, Los Alamos National Lab
[2]Office of Science, United States Department of Energy
[3]Ira A. Fulton Schools of Engineering, Arizona State University

[a)]Corresponding author: cjenkins@lanl.gov

Abstract. Unpredicted bearings failures can be costly and dangerous. Current methods have been examining the use of machine learning algorithms to automatically detect bearing faults. Vibration specialists must react daily, as the sheer number of bearings and the machines they operate are critical and any downtime will result in loss of productivity and endanger personal. The method presented in this paper utilizes a novel approach to detect and determine bearings fault diameters. The detection algorithm uses the cubic support vector machine (SVM) for high accuracy inner and outer race fault detection. After detecting the type of fault, the data is then passed through a second layer that uses a modified K-means clustering and a linear interpolation to accurately estimate the diameter of the fault that was detected.

INTRODUCTION

Bearing faults plague all types of rotating machinery, from fume hood exhaust fans and massive industrial pumps to simple computer fans. These bearings introduce a point of failure at a rate that varies largely depending on operating conditions and preventative maintained practices. No matter how well maintained a bearing is, its eventual failure can lead to high repair costs and even infringe on employee and laboratory health and safety. Traditional methods compare current vibration data from bearings to a previous healthy reading to see the overall change in health[1]. These methods tend to be accurate, but still require a human to diagnose bearing faults. This papers method removes the need to have a healthy baseline reading and instead utilizes data acquired from accelerometers to both diagnose the bearing fault, and then determine the diameter of the fault to help estimate the remaining bearing life.

DATA ACQUISITION

To keep the algorithms simple and generic, the training data used is purely from accelerometers. Data was supplied mostly by Case Western and the Society for Machinery Failure Prevention Technology (MFPT). Different data sets were used to ensure the algorithms would work generically to any machine and not be over trained to a particular one. The Case Western data sets also provided multiple data sets at differing fault diameters created by electro-discharge machining, a method with very tight tolerances (EDM)[2]. Data was also acquired manually from machines exhibiting fault conditions installed at Los Alamos National Laboratory to further test the algorithms. The type of fault acquired was known for these machines, but the fault diameter was unable to be measured due to constraints on destructive testing.

Accelerometers operating at varying frequencies between 9 kHz and 48 kHz were used to acquire test data. The Nyquist frequency of the bearings depends on the type of fault, and varies with bearing properties and machine run speed. The calculations for the different frequencies bearing faults occur at are shown in equations 5-8.

FAULT DETECTION

The goal of the fault detection layer is to differentiate between inner, outer, and healthy readings. The layer was trained using MFPT data sets which includes healthy (labelled baseline), inner, and outer race fault data but has no indication on the diameter of the fault. In total, 14 data sets were used, two with healthy readings and six outer and inner race faults. Six test data sets were obtained from the MFPT data sets and another 22 were obtained from Case Western for a total of 28 test runs.

To improve signal to noise ratio and ensure generality for any machine regardless of run speed, spectral kurtosis[3] was used to create a band pass filter for each data set. Spectral kurtosis is a technique that pinpoints the frequency bands that have the highest number of transients. It then recommends filter bands to remove that contain a high amount of stationary data. Kurtosis has been demonstrated[3] to improve signal to noise ratio for rolling element analysis and is adaptable to any machine type making it a very powerful tool. Spectral kurtosis does not require a baseline reading, giving it an advantage over traditional methods to improve the signal to noise ratio.

After band pass filtering the data using the bands recommended by performing spectral kurtosis, the envelope spectrum of the signal is calculated. Envelope analyses is an established method for bearing fault detection[5,6]. To train the machine learning algorithms, relevant features need to be extracted. The fault detection algorithm uses two features, the log of the ratio of the first inner and outer race fault amplitudes, and the log of the ratio of the second inner and outer race fault amplitudes. These two features were used for their ease in fault detection and improved accuracy. The ratio of the inner and outer race fault amplitudes can directly indicate which fault type has the greater amplitude and by extension what the type of fault the system has. After taking the log of the ratio, it separates the data into three clusters. The negative cluster indicates inner race faults, the cluster around 0 indicating healthy readings, and the positive clustering indicates an outer race fault.

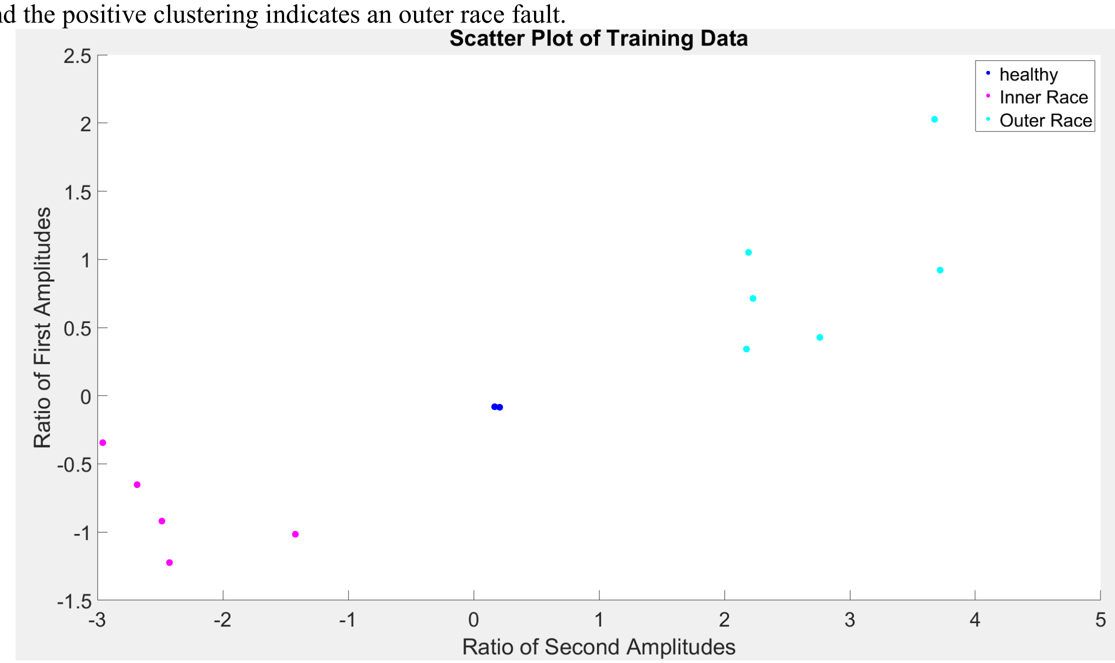

FIGURE 1. Scatter plot of training data used for the first layer detection algorithm. Healthy readings in blue (center), inner race faults in purple (bottom left), outer race faults in cyan (upper right). Axis are the two features used, ratio of the first inner and outer race fault amplitudes and ratio of the second inner and outer race fault amplitudes.

The classification algorithm used is the cubic support vector machine. While the cubic SVM and other algorithms had similar or tied accuracies on the train data, the cubic SVM was better optimized to differentiate between baseline data and faults more accurately. The algorithm achieved a 96% accuracy on the test datasets, mislabelling a baseline reading as an outer race fault.

PREDICTIVE MAINTAINCE

The predicative maintenance layer attempts to estimate fault diameter by calculating the distance a test point falls between clusters of data. The data clusters were obtained from the Case Western datasets and had inner and outer race faults of .007, .014, and .021 inch diameter. The type of bearing and bearing location varied between data sets, with half the data coming from drive end bearings and half from fan end bearings. This ensured the generality of the algorithms for any bearings and not just the ones observed here.

After detecting the type of fault, the accelerometer data is then passed into the respective second layer that can estimate the fault diameter. The features used to train the algorithm differs from the fault detection algorithms. Three new features were chosen for their improved accuracy and distinct clustering, the cage train frequency, rolling element frequency, and the log of the ratio of the first outer and inner race fault amplitudes.

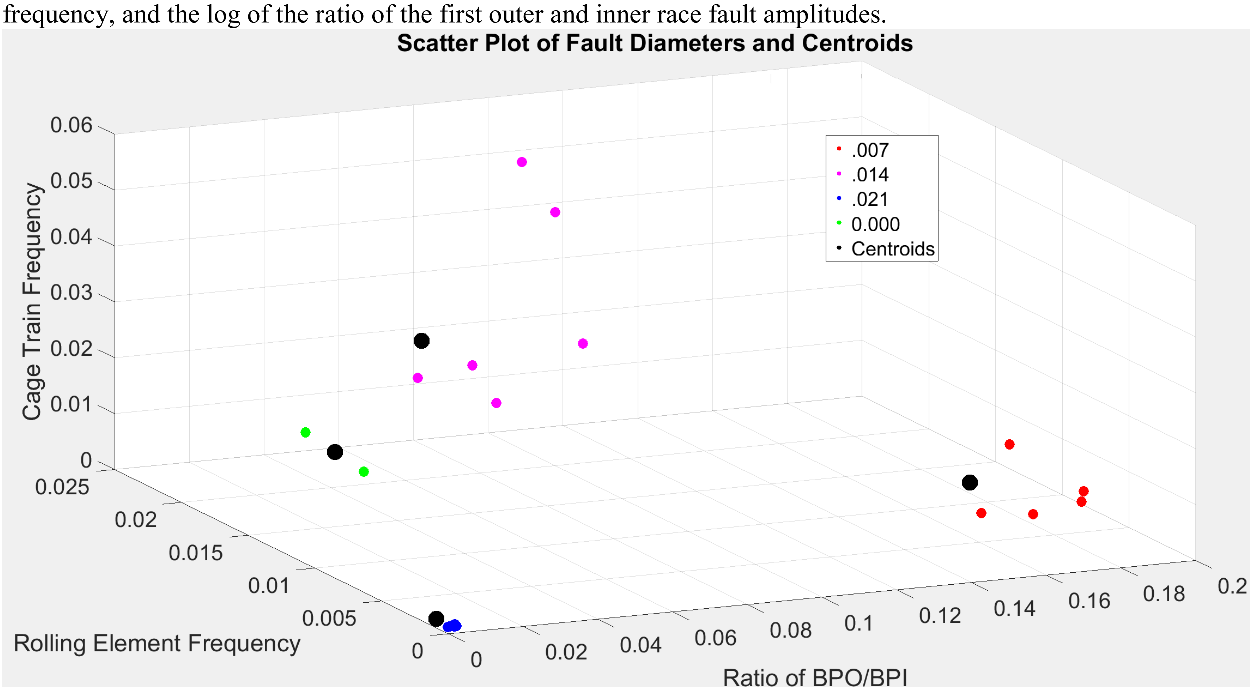

FIGURE 2. 3D scatter plot of training data for fault diameters. Large points in black are the centroids, smaller clusters are different fault diameters. Clusters found using K-means clustering algorithms. Axis are 3 features used.

K-means clustering was used to find the centroid locations for each cluster of data. The algorithm is modified to use the city block distance. K-means is dependent on initial conditions, to reduce the potential of finding local minimums, the algorithm uses 15 seeded points as its initial guesses.

To determine the diameter of the fault, the algorithm estimates the distance a point falls between the two nearest centroids. It finds the vector pointing from the closest centroid to the second closest centroid $\vec{V}$. It then finds the vector from the nearest centroid to the test point $\vec{R}$. After finding the two vectors, we then find the projection of $\vec{V}$ in the direction of $\vec{R}$.

$$Z=\vec{R}\cdot\hat{V} \quad 1)$$

It then finds the new vector in the direction of $\hat{R}$ with magnitude Z.

$$\vec{Z}=Z*\hat{V} \quad 2)$$

After finding the projection onto $\vec{V}$, we find the ratio X of projection to the total vector.

$$X=\frac{\vec{Z}}{\vec{V}} \quad 3)$$

We can use the ratio X in a linear interpolation with the labelled diameters of the two nearest centroids to estimate the amount of wear. With K being the labelled diameter of the nearest centroid, and J the labelled diameter of the second closest centroid, the linear interpolation is set as the equation below:

$$D = (J - K)X + K \qquad 4)$$

Equation 4 directly outputs the diameter of wear of the bearing fault without needing to compare the fault data to previous healthy readings from the same bearing.

Calculations

$$\mathrm{BPFO}=\frac{N*S}{2}\left(1-\frac{B}{P}\cos\theta\right) \qquad 5)$$

Calculation for the ball pass outer frequency occurring at outer race faults

$$\mathrm{BPFI}=\frac{N*S}{2}\left(1+\frac{B}{P}\cos\theta\right) \qquad 6)$$

Calculation for the ball pass inner frequency, occurring at inner race faults.

$$\mathrm{CTF}=\frac{S}{2}\left(1-\frac{B}{P}\cos\theta\right) \qquad 7)$$

Calculation for the cage train frequency, used for calculating fault diameters

$$\mathrm{REF}=\frac{P*S}{2*B}\left(1-\left(\frac{B}{P}\right)^2\cos\theta^2\right) \qquad 8)$$

Calculation of the Rolling element frequency, used for calculating fault diameters

N-Number of balls
S- Revolutions per second
B-Ball diameter
P-Pitch diameter
θ-Contact angle

CONCLUSION

The goal of the project was to design a layered detection algorithm that can predict bearing fault diameters based solely on accelerometer data. Accelerometer data was chosen due to being easy to obtain remotely and automatically, and the abundance of datasets that are available. The first layer uses cubic SVM to differentiate between inner, outer, and healthy bearing readings. After the determination of the type of fault, the second layer then uses the same data to estimate the diameter of the fault. The estimation algorithm uses unsupervised K-means to find clusters of data with different fault diameters, then uses vector calculus and linear interpolation to directly output the diameter of fault.

The fault detection layer operates with a high accuracy of 96% on the test data sets, and 100% on the training set. The use of an optimized cubic SVM greatly improved the accuracy of the detection algorithm over similar methods like quadratic discriminate. The algorithm was trained using different machines operating with different bearings at varying speeds to ensure the algorithms were not over fit for a single machine. The algorithm uses two features, and can be scaled to use more in higher dimension space if needed. Diminishing returns were found as more features were added, as just the log of the ratio of the first amplitudes was enough to gain more than 80% accuracy on the test data sets. The addition of the second feature, the log of the second amplitudes increased the accuracy to almost 100% on the test data.

The fault diameter estimation layer offers a novel approach using a modified K-means algorithm to estimate the diameter of bearing faults. The algorithm uses K-means to find clusters of different fault diameters. It then compares the distance a point falls from the two centroids to estimate the inner or outer race fault diameter. While the method used was only trained using three features and in three dimensional space, it can be scaled to operate with any number of features in higher dimensional space for possible improved accuracy. The algorithm using the three features managed to achieve 12% error. The mean difference the algorithm's estimation was from the known fault diameters was 8.017e-4, which is close to the standard tolerances used for the machining process. While the algorithm must introduce some amount of error, it is undeterminable whether the dominate source is through the machining tolerances or the algorithm itself.

The advantage this method offers over traditional vibration analysis is that it does not require a healthy baseline reading to work. Traditional methods involve comparing current values of different features with previous baseline values. Using traditional methods only works if the baseline value is available to compare to, and requires extra work by a specialist to gather and store data. The method outlined in the paper can be recorded remotely and done automatically without the requirement to send a specialist in at all. Many building automation systems are installing accelerometers and other sensors directly into fans. Using these sensors, it would be easy to monitor live data for early signs of faults, and then estimate their progression as the algorithm monitors their increasing diameter. The method can ease the burden of monitoring bearings for maintenance staffs coupled with active detection and monitoring. The cost of installing these sensors and beginning to live monitor data is much less than the cost of a run to failure approach, and greatly reduces the dangers to both staff and experiments it brings.

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